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Assessing the Soil Carbon, Biomass Production, and Nitrous Oxide Emission Impact of Corn Stover Management for Bioenergy Feedstock Production Using DAYCENT

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Abstract Harvesting crop residue needs to be managed to protect agroecosystem health and productivity. DAYCENT, a process-based modeling tool, may be suited to accommodate region-specific factors and provide regional predictions for a broad array of agroecosystem impacts associated with corn stover harvest. Grain yield, soil C, and N_2O emission data collected at Corn Stover Regional Partnership experimental sites were used to test DAYCENT performance modeling the impacts of corn stover removal. DAYCENT estimations of stover yields were correlated and reasonably accurate (adjusted r^2=0.53, slope=1.18, p<<0.001, intercept=0.36, p=0.11). Measured and simulated average grain yields across sites did not differ as a function of residue removal, but the model tended to underestimate average measured grain yields. Modeled and measured soil organic carbon (SOC) change for all sites were correlated (adjusted r^2=0.54, p<<0.001), but DAYCENT overestimated SOC loss with conventional tillage. Simulated and measured SOC change did not vary by residue removal rate. DAYCENT simulated annual N_2O flux more accurately at low rates (≤2-kg N_2O-N ha^{-1} $year^{-1}$) but underestimated when emission rates were >3-kg N_2O-N ha^{-1} $year^{-1}$. Overall, DAYCENT performed well at simulating stover yields and low N_2O emission rates, reasonably well when simulating the effects of management practices on average grain yields and SOC change, and poorly when estimating high N_2O emissions. These biases should be considered when DAYCENT is used as a decision support tool for recommending sustainable corn stover removal practices to advance bioenergy industry based on corn stover feedstock material.

Keywords DAYCENT · Soil carbon change · Corn stover · Bioenergy · N_2O emissions

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Introduction

Corn (*Zea mays* L.) stover, the plant residue remaining after harvest, is an attractive source of biomass for bioenergy in the USA. The US Department of Energy Billion-Ton Study Update (2011) considers agricultural residues such as corn stover to be among the best sources of raw material to support bioenergy industry, as they are already produced on a large scale at low costs in regions with established crop production infrastructure. Corn stover currently accounts for ~70 % of all crop residue production in the USA and is therefore of high interest as a feedstock to support the expansion of industrially scaled bioenergy production [1].

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The impetus to expand bioenergy production in the USA, exemplified at the federal level with the Energy Information and Security Act of 2007 and its revised Renewable Fuels Standard (RFSII), includes replacing the use of fossil fuels to strengthen US fuel security, reducing the climate change impact of fossil fuel combustion, and concomitantly enhancing rural development [2]. However, the removal of crop residues to expand bioenergy production must consider potential impacts to the agroecosystem services provided by agricultural by-products like corn stover. While corn stover is widely available in the corn production regions in the USA, care must be taken with residue removal in order to maintain agroecosystem health and productivity [3, 4]. Crop residues influence multiple agroecosystem functions which impact crop productivity, including providing the building blocks for soil organic matter that, in turn, contribute to water and nutrient-holding capacity as well as nutrient availability [5–7]. Crop residues can reduce soil erosion, help maintain soil fertility, and impact greenhouse gas emissions (GHGs), including nitrous oxide (N_2O) and methane (CH_4) fluxes from soil and changes in soil organic carbon (SOC) storage and net carbon dioxide (CO_2) emissions [8, 9]. Corn stover removal can reduce or increase grain yields depending on other land characteristics and management practices [5, 10]. Furthermore, replacing nutrients removed by stover removal can increase fertilizer costs [11]. Sustainable agricultural management practices involving residue use must support a robust bioenergy industry, meet climate impact reduction (e.g., RFSII) standards for renewable fuels, and maintain cropland health to support growing crop production demands.

An economically viable and environmentally sustainable bioenergy industry based on corn stover feedstock must incorporate both crop management practice recommendations for corn stover production as well as accurate predictions of production potential. Past studies evaluated impacts of corn stover removal on subsequent grain yield [5, 7, 12, 13] and used long-term sites to address other ecosystem effects such as SOC changes [14–16]. A research goal of the Sun Grant Initiative's Corn Stover Regional Partnership team—which is also supported by the USDA—Agricultural Research Service's Resilient Economic Agricultural Practices (ARS-REAP) project—was to supplement these studies by establishing an extensive network of field trials across a range of climatic and soil types to assess varying levels of residue removal on soil C, water, nutrient content, and biomass characteristics. More information on the Regional Partnership studies is included within this and previous publications [4, 11, 17].

The Regional Partnership corn stover trials greatly expand the amount of site-specific primary data on corn stover residue production and the agroecosystem impacts of its removal. Empirical data are needed to calibrate, validate, and refine process-based models so they can be used to help establish valid sustainable harvest rate guidelines (Johnson et al. (this issue) and [9]). The need for such data was recognized by the Regional Partnership corn stover team; therefore, the project was designed to support predictive modeling, linking field trial data to expanded regional projections [17].

A modeling tool suited to accommodate region-specific factors and provide regional predictions for a broad array of agroecosystem impacts is DAYCENT. The DAYCENT model, a process-based ecosystem model developed at Colorado State University, simulates GHG fluxes as well as plant/soil C dynamics and many other ecosystem processes [18, 19]. DAYCENT and its predecessor CENTURY have been applied and tested in many agricultural systems both in the USA and globally [20–22], including several types of bioenergy production systems [23–25]. While DAYCENT modeling of corn production has been widely tested for model applications such as estimating agricultural land use emissions for the US Environmental Protection Agency annual GHG inventory report [26], evaluations of its performance simulating the impacts of corn stover harvest are limited. One example is a recent study by Gao et al., where DAYCENT was applied as part of a Michigan-specific life cycle assessment (LCA) of corn stover management [27].

There is a critical need for the application of process-based models such as DAYCENT in designing scientifically sound decision support tools for the development of bioenergy feedstock production [28]. Therefore, members of the Regional Partnership team completed a review to identify economic and sustainability metrics that impact the potential for corn stover residue harvest in the Midwest [29]. Based on this review [29], an integrated stover removal tool was designed that linked several existing models (i.e., the Revised Universal Soil Loss Equation Version 2 (RUSLE2), the Wind Erosion Prediction System (WEPS), and the Soil Conditioning Index (SCI)) to predict maximum residue removal rates that would meet multiple sustainability criteria [30]. Recently, the DAYCENT model was integrated into this framework to provide dynamic estimates of biomass yields, SOC changes, and GHG fluxes, thereby refining the evaluation and recommendation of "sustainable" residue removal rates on regional and site-specific levels. Evaluating DAYCENT simulations of corn stover residue removal effects against empirical data from the Regional Partnership field sites contributes to the development of the sustainability assessment tool that can provide region-specific recommendations to support agroecosystem services and the bioenergy industry.

Balancing agroecosystem services and developing a viable large-scale bioenergy industry will require changing management practices (e.g., growing cover crops and modifying fertilizer form or rate) to increase or supplement C and nutrients in the system. Cover crops and manure application [31, 32], increased synthetic N fertilizer application [33, 34], and reduction in tillage intensity [6, 14] have been identified as amelioration approaches to develop "sustainable" practices for corn residue harvest [29, 35] and subsequently are recurring focal treatments in field studies assessing corn stover management. In this study, we evaluated DAYCENT performance in simulating SOC change, corn grain and stover yields, and direct N_2O emissions—a powerful greenhouse gas [36]—from soils against the measured data from three of the Regional Partnership corn stover sites and two long-term published corn stover removal experiments [6, 10, 16, 37–41]. For the current study, simulated treatments were based on site-specific variation in residue removal rates, tillage, N fertilizer, and cover crops. We focus our analyses on the overall DAYCENT performance in these systems, as well as on the measured versus modeled impacts of residue removal rates combined with variation in tillage treatments.

Materials and Methods

Experimental Data

To test the performance of the DAYCENT model, a series of data were assembled from published literature evaluating two sites in Rosemount, MN and Morris, MN for the soil and crop production impacts of long-term corn stover removal, as well as different levels of nitrogen (N) fertilizer application and types of tillage [6, 16, 37, 38]. Data were also assembled from three Corn Stover Regional Partnership sites in Ithaca, NE, Brookings, SD, and a different site in Morris, MN established as a subset of ARS-REAP to evaluate the sustainability of corn stover harvest [17]. The Regional Partnership sites test multiple levels of residue removal combined with differences in tillage, N fertilizer application, and cover crop management practices and are described in greater detail in this issue as well as in prior publications [10, 40, 41]. Measurements at the Regional Partnership sites included grain and stover yields, SOC change from 0 to 20 cm, and direct soil N_2O emissions (Table 1). The Regional Partnership data and published literature values allowed us to test DAYCENT's performance in simulating biomass (i.e., grain and stover) production, SOC change, and N_2O emissions.

DAYCENT Model Overview

The DAYCENT model runs on a daily time step and simulates various ecosystem processes to a soil depth of 20 cm. The model includes routines for simulating the movement of soil nutrients, the movement of water through soil layers, plant growth, and many other ecosystem components that are described in greater detail elsewhere [20]. The key drivers of DAYCENT include maximum and minimum daily temperature, daily precipitation, soil texture, and land management (including specific plant types grown and soil management such as tillage and nutrient additions).

The DDcentEVI version of DAYCENT (a version of DAYCENT with the option to use Enhanced Vegetation Index— i.e., EVI—data) was used for this analysis. DDcentEVI was developed and tested to estimate total agricultural land use emissions for the US Environmental Protection Agency's (EPA) GHG emission inventory annual report [26]. This repeated annual set of simulations involve model parameterization for common agricultural crops, including corn and soybean, as well as millions of model runs and established protocols for estimating model uncertainty [42–44], documented in detail in Annex 3.12 of the most

Table 1 Summary of study locations and treatments

Source	Location	Latitude/ Longitude	Management description	Grain yield	Stover yield	Soil C	N_2O
[16, 37]	Morris, MN	45.6/−95.9	29-year-continuous corn; moldboard tillage; low fertilizer (83 kg N ha^{-1}), high fertilizer (166 kg N ha^{-1}), and control (0 kg N ha^{-1}); *0 and 100 % stover removal*	X	X	X	-
[6, 38]	Rosemount, MN	44.7/−93.1	13-year-continuous corn; chisel, moldboard and no till tillage; 0 and 200 kg N ha^{-1}, *0 and 100 % stover removal*	X	X	X	-
Regional Partnership: Swan Lake experimental site	Morris, MN	45.7/−95.8	7-year-corn/soy rotation; chisel and no till tillage; 130 kg N ha^{-1}; *0, 50, and 100 % stover removed*	X	X	X	X
Regional Partnership: University of Nebraska Agricultural Research and Development Center[10, 39]	Ithaca, NE	41.2/−96.4	13-year-continuous corn; no till tillage; 60, 120, and 180 kg N ha^{-1}; *0 and 100 % stover removed*	X	X	X	X
Regional Partnership: North Central Agricultural Research Laboratory [40, 41]	Brookings, SD	44.3/−96.8	7-year-corn/soy rotation; no till tillage; average 135 kg N ha^{-1}; *0,~29, and ~97 % residue removal*, with and without cover crop	X	X	X	X

recent inventory report [26]. Given the extensive parameterization process with DDcentEVI, we chose to use this version in order to focus our efforts on validating model performance using all data for corn stover residue removal experiments available for this analysis.

An important component of any DAYCENT model simulation is initializing the model based on the native ecosystem type expected for the specific site and using the best available information about land management after the native ecosystem is converted for agricultural use. Given temperature and precipitation as key drivers of biogeochemical processes, the longest possible continuous daily climate datasets are needed to run model initializations as well as drive simulations for the experimental periods of interest. The climate data used to drive model simulations for this study were derived using the latitude and longitude of site locations to determine the nearest North American Regional Reanalysis (NARR) grid cell and the associated daily maximum and minimum temperatures and total precipitation from 1979 to 2009. The NARR data, given at a 32-km scale, were generated as an extension of the National Centers for Atmospheric Research Global Reanalysis project and are freely available online (http://www.emc.ncep.noaa.gov/mmb/rreanl/). The NARR data are generated using algorithms to interpolate weather for areas between weather stations. The NARR dataset is the standard used for simulations in the US GHG inventory and therefore was the source of climate data for all sites and years in this analysis where site-specific data were not available. For the three Regional Partnership sites, site-specific daily weather data were available for the experimental time periods, and these data were used instead of the NARR weather data in the years available, extending the climate data time period at these sites to 2010.

Soil texture information was gathered either from direct field measurements reported by the Regional Partnership sites or from soil texture data reported in publications for the two non-Regional Partnership sites. Prior land use history used for model initialization was drawn from (1) county-level native vegetation assumptions used in simulations for the EPA GHG emission annual report and (2) information gained from literature and personal communication for agricultural management from when native vegetation was converted into cropland up to the treatment period. Experimental management practices, such as planting and harvest dates, dates and quantities of fertilizer application, and corn stover harvest rates, were drawn from reported literature and the Regional Partnership field data. These land use data were used to schedule events within the DAYCENT model simulations. A total of 53 different corn stover management scenarios, matching experimental management practices across the five experimental sites, were simulated to generate model results to compare against measured data.

Statistical Analyses

Statistical analyses were completed using R-2.15.1 software as well as the Hmisc and car packages [45–47]. Regression analyses were applied to compare measured versus modeled grain yield (megagram C per hectare), stover yield (megagram C per hectare), SOC change over the measurement period (megagram C per hectare), and annual N_2O flux (kilogram N_2O–N per hectare per year) across all sites and all years. Two treatment effects were also selected for measured versus modeled estimate evaluation: (1) residue removal level and (2) residue removal level+tillage. For measurements taken across multiple years, averages by treatment were used to compare measured versus modeled results across all sites. For the evaluation of residue removal level alone, measured versus modeled estimates of grain C and SOC change were compared for three stover removal levels: full removal (100 %), moderate removal (29–50 %), and no removal (0 %). Soil N_2O emissions were evaluated using two treatment levels: stover removal (>0 %) and no removal (0 %). For the evaluation of residue removal level+tillage, measured versus modeled estimates of grain C and SOC change were compared using four levels: conventional tillage+0 % removal, conventional tillage+>0 % removal, no tillage+0 % removal, and no tillage+>0 % removal. Measured versus modeled estimates were assessed for normality using a Shapiro–Wilk test, as well as assessed for equal variance. These measured versus modeled estimates were then assessed across these treatment effects using type III sums of squares two-way analyses of variance (ANOVAs) to account for unequal sample sizes, where the fixed effects tested were residue removal level and tillage.

Results

Biomass

DAYCENT simulated annual grain yields with significant correlation with measured yields but with high dispersion and significant bias—there was a significant positive intercept and a slope less than 1 (Fig. 1a). DAYCENT simulated annual stover harvest with a tighter significant correlation and less bias, with a slope closer to 1 and an insignificant intercept (Fig. 1b).

The measured and modeled average grain yields across the sites did not differ between residue removal levels (Fig. 2a, $p>0.05$). Across all treatment levels, measured values were significantly higher than modeled estimates (Fig. 2a, $p=0.012$). Measured and model estimates of average grain yields did not show a significant overall effect of tillage+residue removal levels, measured versus modeled estimates, or a significant interaction between these factors (Fig. 2b, $p>0.05$).

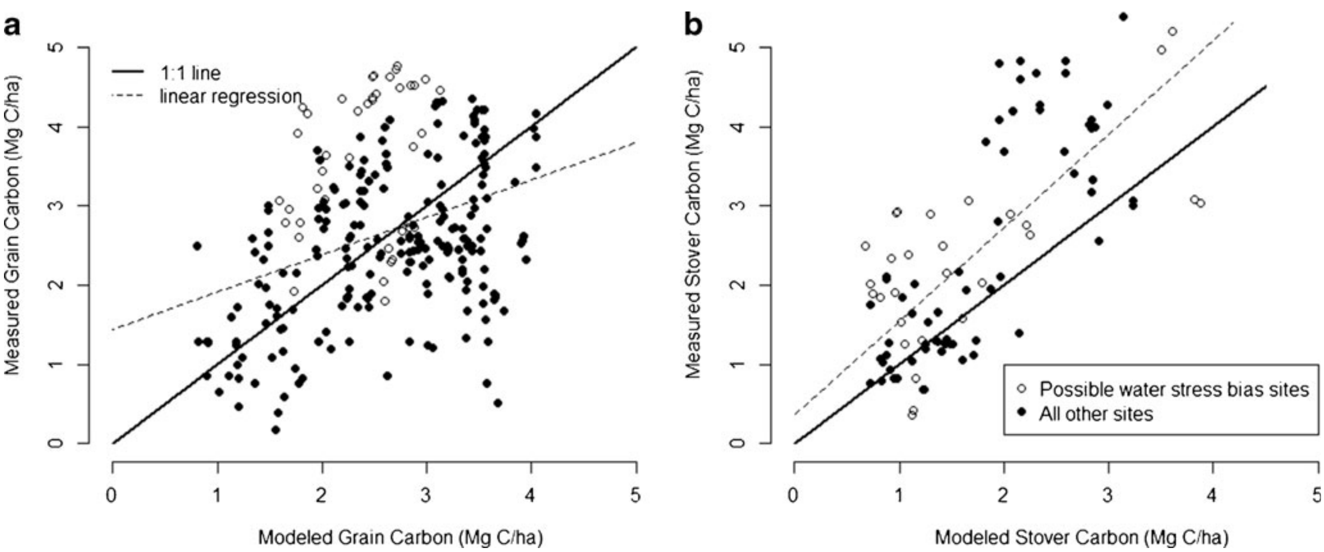


Fig. 1 Measured versus modeled grain yields (**a**) and corn stover harvest (**b**) for all treatments and all years for which daily weather data was available. The grain comparison (**a**) shows a significant relationship and intercept (adjusted r^2=0.13, slope=0.47, intercept=1.43, p<<0.001; root-mean-square error (RMSE)=0.95). The stover comparison (**b**) shows a significant relationship but insignificant intercept (adjusted r^2=0.53, slope=1.18, p<<0.001; intercept=0.36, p=0.11; RMSE=0.90)

Soil C Change

The modeled and measured SOC change for all the sites exhibited a significant correlation but a deviation from the 1:1 linear relationship, with a significant positive intercept and slope less than 1 (Fig. 3a). Excluding sites that had ten or fewer years between initial and final SOC measurements (Fig. 3b), and thus greater uncertainty in the magnitude and direction of change, gave a tighter correlation between measured and modeled estimates. However, removing short-term sites did not change the model overestimation of SOC loss rates for sites where measured SOC stocks were declining, with a less significant positive intercept and a lower slope (Fig. 3b).

For treatments where the time between initial and final SOC measurements exceeded 10 years, SOC change did not vary significantly by residue removal rate or by the interaction between the residue removal rate and the measured versus modeled estimates (Fig. 4a, p>0.05). However, measured versus modeled estimates did differ significantly, with the model consistently overestimating SOC change in the same direction as the measured data (Fig. 4a, p<<0.001). For these

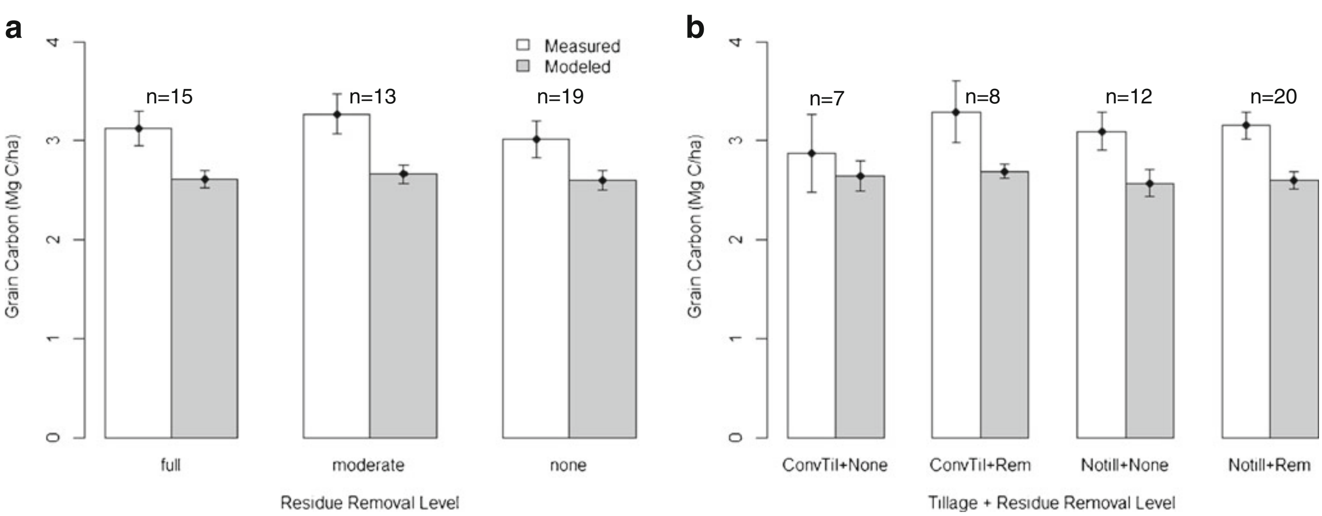


Fig. 2 Modeled versus measured grain yields by three levels of residue removal rates (100 %=full, 100 %>moderate>0 %, and 0 %=none) (**a**), as well as four levels of combined tillage (conventional versus no tillage) and residue removal (0 %=none vs >0 %=rem) (**b**). *Error bars* show standard error, with the number of replicates reported above each set of measured versus modeled comparison

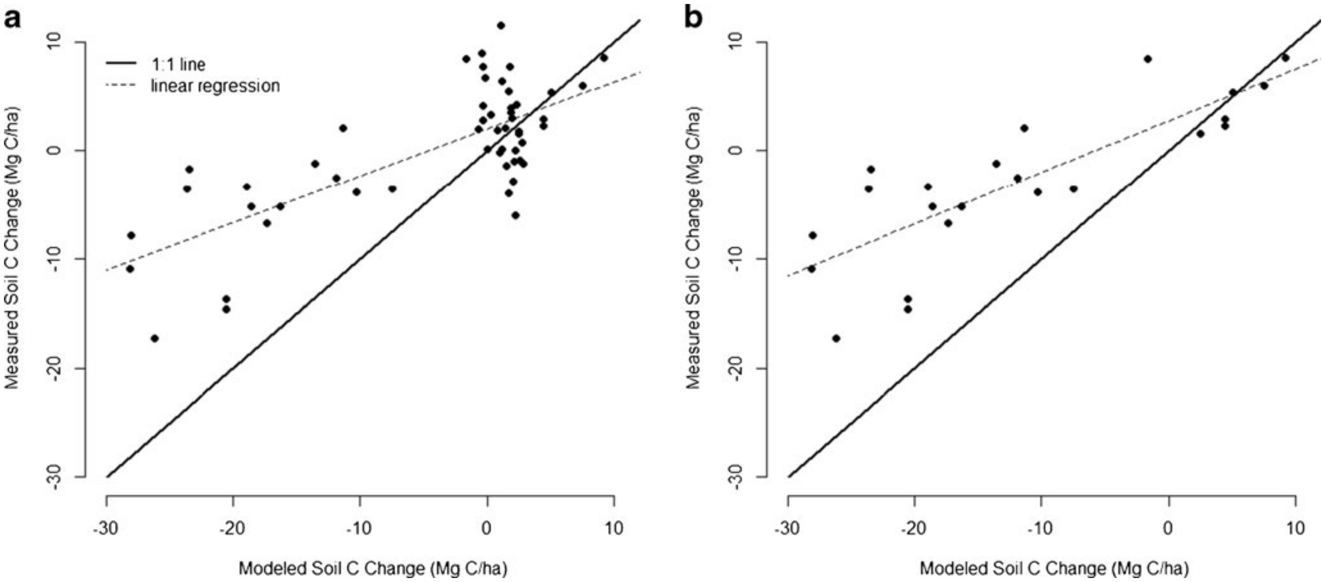


Fig. 3 Measured versus modeled SOC change from 0 to 20 cm for all sites and all treatments (**a**) and for sites and treatments with greater than 10 years between initial and final SOC measurements (**b**). All sites (**a**) show a significant relationship and intercept (adjusted r^2=0.54, slope=0.43, p<<0.001; intercept=1.97, p=0.002; RMSE=4.03). Sites with longer SOC measurements (**b**) show a significant relationship and slope, but a weakly significant intercept (adjusted r^2=0.67, slope=0.48, p<<0.001; intercept=2.7, p=0.03; RMSE=3.89)

same treatments, SOC did vary significantly by tillage+residue removal level and measured versus modeled estimates alone, as well as by the interaction between these factors (Fig. 4b, p=0.003, p=0.003, and p=0.006, respectively). Both the measured and modeled data suggest that conventional tillage leads to a loss of SOC, while no tillage leads to a gain or little change in SOC that may depend on whether residue is removed. However, the model shows a clear bias of overestimating SOC loss with conventional tillage and with or without residue removal.

N_2O Emission

Modeled versus measured annual N_2O emissions showed a significant relationship and an intercept that did not differ significantly from 0, but the slope>1 indicates a model bias of underestimating annual N_2O emissions. The increasing divergence from the 1:1 line between modeled and measured values with higher measured emission rates suggests better DAYCENT performance in low-emission systems (<2-kg N_2O-N ha^{-1} year^{-1}) but underestimation for sites and years

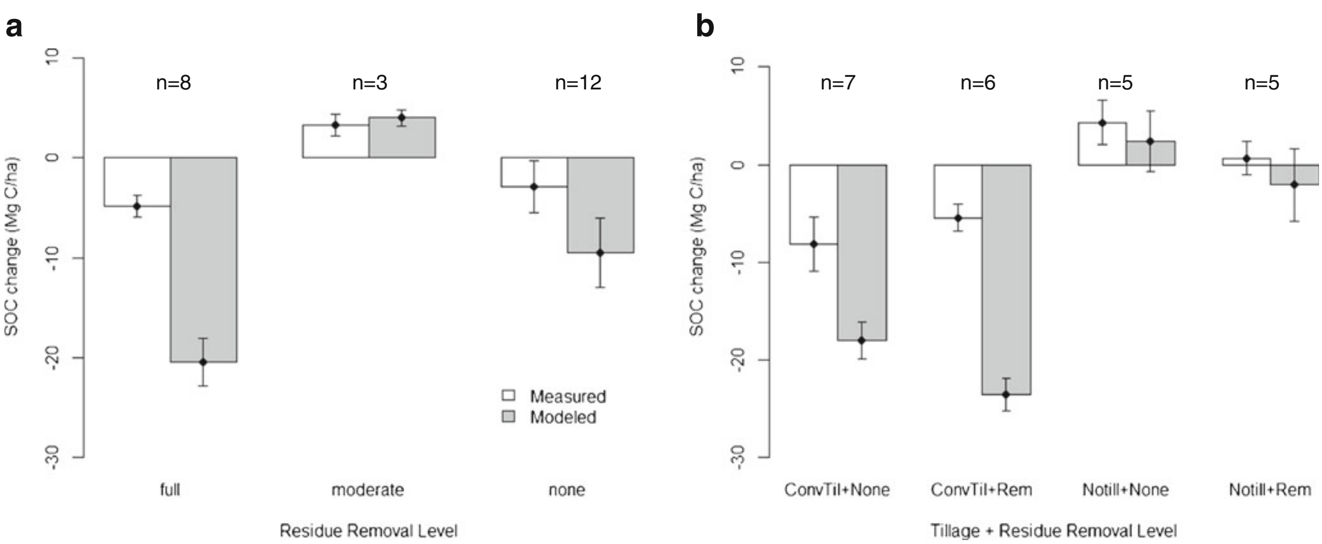


Fig. 4 Modeled versus measured SOC change at sites with >10 years between initial and final SOC measurements from 0 to 20 cm by three levels of residue removal rates (100 %=full, 100 %>moderate>0 %, and 0 %=none) (**a**), as well as four levels of combined tillage (conventional vs no tillage) and residue removal (0 %=none vs >0 %=rem) (**b**), showing standard error

with high emission rates (i.e., >3-kg N_2O-N ha^{-1} $year^{-1}$) (Fig. 5a). There were no significant differences in N_2O as a function of residue removal in either the measured or modeled estimates (Fig. 5b, $p>0.05$ for all factors).

A qualitative comparison of measured versus modeled estimates of daily N_2O emission shows no obvious pattern of divergence between the daily modeled and measured values when N_2O emissions are low (Figs. 6 and 7). However, there is substantial divergence when N_2O emissions are in peak periods. DAYCENT sometimes simulated peak periods with similar timing to measured peak periods but underestimated their magnitude (Figs. 6b and 7c). DAYCENT simulation of peaks sometimes did not match the timing of measured peaks (Figs. 6d and 7b). DAYCENT also failed to simulate some peak periods reflected in the measured data (Figs. 6b and 7a, b).

Discussion

Biomass

Modeled results suggest that DAYCENT can reasonably simulate corn stover yields across the management practices considered in this study, a key concern for the expansion of the bioenergy industry based on corn residue as a feedstock material. However, the slope did exceed 1—the value that would reflect perfect model simulation of measured values—indicating some bias toward DAYCENT underestimating stover yields that should be considered in the use of the DAYCENT model results within the context of a bioenergy decision support tool.

DAYCENT performed more poorly in simulating annual grain yields. The low coefficient of determination (r^2) reflected high dispersion, and the model tended to overestimate grain yields in years where measured grain yields were low and underestimate grain yields in years where measured grain yields were high (Fig. 1a). DAYCENT simulates the growth of aboveground biomass based on the interactions between moisture and temperature and then simulates grain harvest based on the harvest index specified by the user. Fine-scaled timing-specific interactions between temperature, moisture, and grain yields (e.g., high or low precipitation or temperature events that impact flowering or grain filling) are not yet included in DAYCENT and may cause its variable performance simulating annual grain yields. When the data were aggregated across years, DAYCENT did successfully simulate the overall nonsignificant impact of corn stover residue removal levels across these treatments; however, the significant difference between modeled versus measured results indicates an overall model bias of underestimating grain yields (Fig. 2a). This bias was not apparent in the comparison between measured versus modeled grain yields across combined tillage and residue removal levels; in this analysis, the model successfully captured the overall insignificant impact of residue removal levels and tillage on grain yields, with no significant difference between measured and modeled results (Fig. 2b).

These results suggest that DAYCENT can be used to successfully model the relative impacts of residue removal on grain yields but should be used carefully if simulating quantities of grain yield on an annual basis. The DDcentEVI version of DAYCENT has shown a tendency to overestimate water stress effects on the grain production in the northern

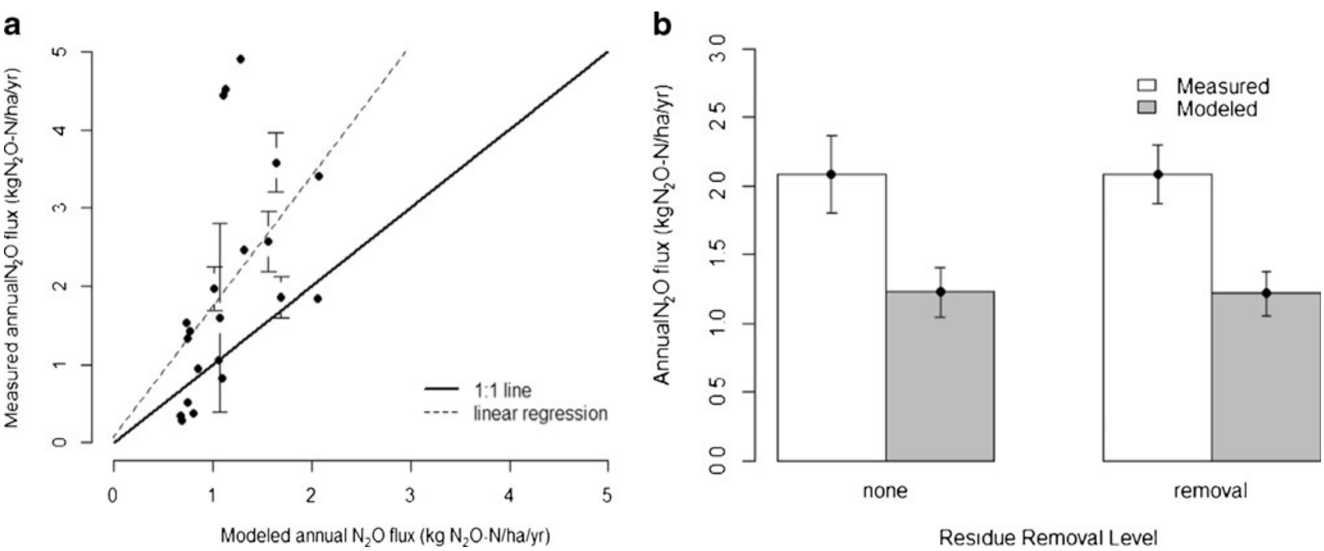


Fig. 5 Measured versus modeled annual N_2O flux for two sites (**a**) showing measured standard error where reporting made these data available, a significant relationship, and an insignificant intercept (adjusted $r^2=0.22$, slope=1.67, $p=0.019$; intercept=0.078; RMSE=1.2). *Bar graph* (**b**) shows measured versus modeled mean annual N_2O flux by residue removal level (none=0 % stover harvest ($n=3$), removal=>0 % stover harvest ($n=4$)), with standard error

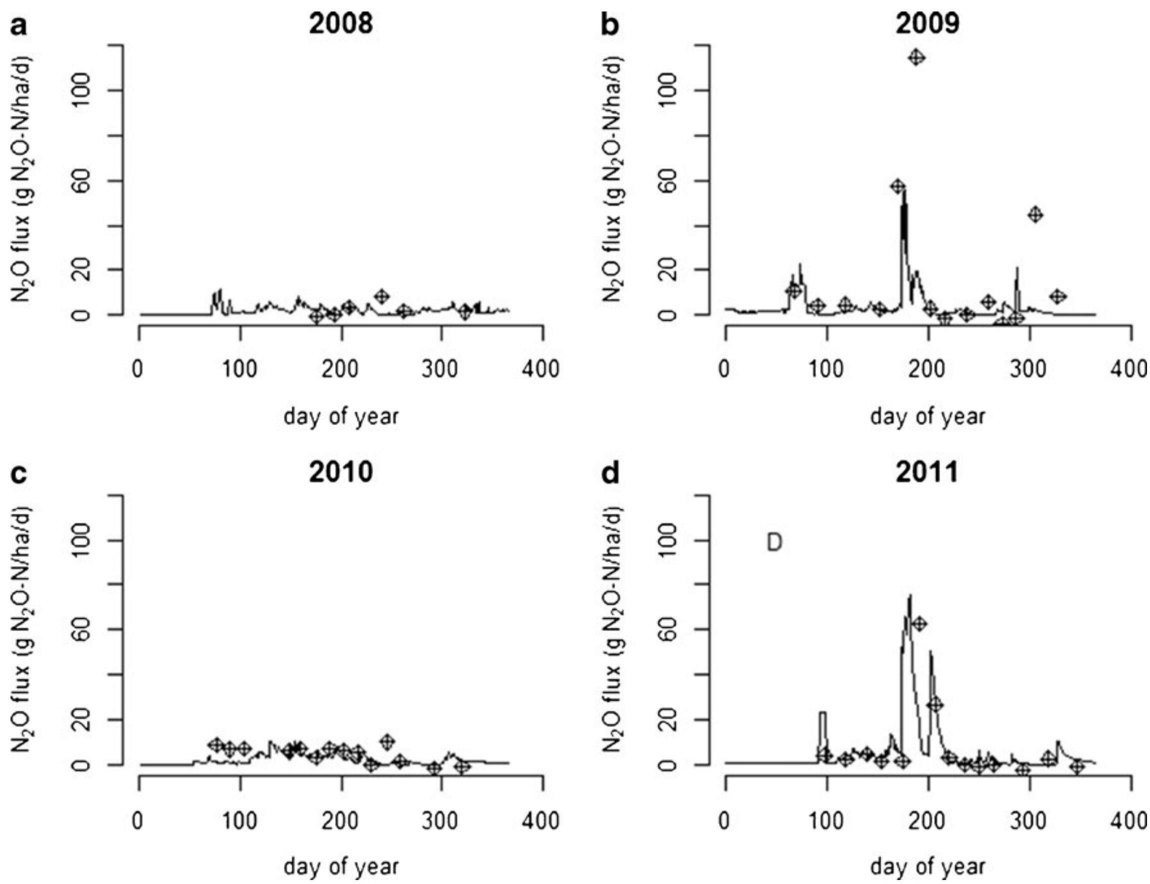


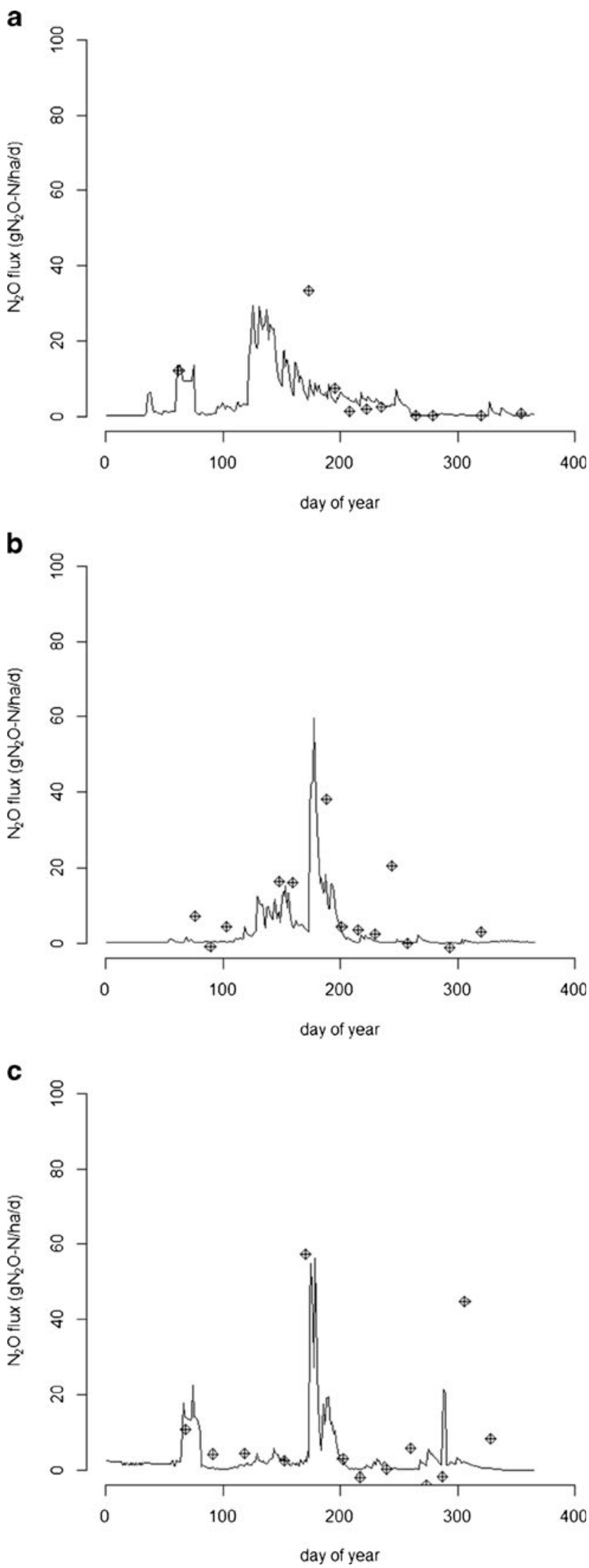
Fig. 6 Daily N_2O flux measurements (*hatched diamonds*) compared with daily model simulations (*line*) of N_2O flux for one representative site under 4 years of corn—soybean rotation, with no residue removal in soybean years (**a**, **c**) and partial residue removal during corn years (**b**, **d**)

Midwest region (Steve Williams, personal communication). This region was the location of several sites used in this study that showed substantial model underestimation of annual grain yields relative to measured values (open circles, Fig. 1a). This model bias should be addressed for evaluating sustainability factors for corn stover residue harvest in the northern Midwest region, with a better representation of water stress effects on grain yields—particularly, better representation of the effects of precipitation timing, which can be critical for grain production—to alleviate this bias in the modeled results.

Soil C Change

The DAYCENT model had variable performance modeling SOC change. DAYCENT simulations matched the direction of SOC change for most sites (Fig. 3a), particularly sites with greater periods of time between initial and final SOC measurements used to calculate SOC change (Fig. 3b). DAYCENT results, however, showed increasing divergence from measured values showing SOC losses (Fig. 3). Soil C is highly heterogeneous and variable, and often, longer periods of time are required to effectively measure and observe SOC changes due to changes in land management. The sites in this study with shorter time sets had greater measured variation than that reflected in the modeled estimates, which tended to model treatments at these sites as just above or below 0 change (Fig. 3a). It would be useful to repeat the measurement of SOC at these sites in the future to assess the accuracy of model simulations over a longer time period. The sites might experience more SOC change following near-term management changes than what the model is predicting, but the model might account for some of this SOC change if it simulates the effects of the practice (such as increased decomposition) longer than the site experiences. Alternatively, the model may be underestimating total changes occurring with the management practices at these sites. The modeled versus measured comparison of SOC changes over a longer time period (e.g., 10 years or greater, as what were available for the other sites in this analysis) would address this question, with either an

Fig. 7 Daily measured (*hatched diamonds*) versus modeled (*line*) N_2O ▶ flux for a selection of sites and years where annual emissions calculated from measured values exceeded simulated annual emissions by at least 1.5-kg N_2O-N ha^{-1} $year^{-1}$ (see Fig. 5a), showing examples of model failure to simulate N_2O peaks (**a**, **b**), failure to simulate the timing of N_2O peaks (**b**) and underestimation of N_2O peak magnitude (**c**)



increasing correlation between measured versus modeled results supporting the former behavior of underestimating near-term changes or continued disconnection between modeled and measured SOC change indicating poor model performance in these locations. In the latter case, further model assessment of SOC simulations would be required to identify the cause for these site-specific discrepancies in modeled simulations as compared with measured data.

Measured SOC changes by residue removal show no significant SOC change with different levels of residue removal but suggest greater SOC loss with full residue removal and the potential for SOC gain with partial removal (Fig. 4a). This supports a number of studies suggesting that SOC change can be minimized by partial rather than full residue removal [10, 13, 48, 49]. In contrast, modeled results show the unexpected behavior of the greatest SOC gain with moderate residue removal and the potential for loss with both no and full residue removal (Fig. 4a). However, these results could be due to the interacting effects with the overestimated modeled SOC loss with conventional tillage, which can be observed in Fig. 4b.

DAYCENT captures the measured trend of potential for SOC loss with conventional tillage across residue removal treatments versus some SOC gains with residue treatments combined with no tillage (Fig. 4b). However, the model is clearly overestimating the SOC losses in the conventional tillage treatments (Fig. 4b). Simulated soil decomposition processes in the DDcentEVI version of DAYCENT may be too sensitive to tillage. The comparison of the modeled estimates to the total aboveground and belowground biomass, as well as an analysis of the modeled soil decomposition sensitivity to tillage, would clarify the model processes causing this overestimation of SOC loss. Despite oversensitivity to tillage, our results support other modeled analyses that identified the potential for no tillage management practices to maintain SOC with residue removal [50]. Specifically, our measured and modeled SOC changes indicated a minimal or positive SOC change when no tillage is combined with residue removal, versus a more strongly negative SOC change when conventional tillage is combined with residue removal (Fig. 4b). Numerous studies have focused on combining management practices such as increased N fertilizer and reduced tillage with corn stover residue harvest, in order to maintain yields and soil fertility [5, 14, 33, 34]. In the set of sites analyzed in this study, we were only able to analyze tillage in addition to residue removal for modeled versus measured analyses. While N fertilizer levels were included in some of the experiments considered in this analysis, aggregating data for cross-site comparison between N fertilizer levels was not possible due to differences in experimental designs. The importance of combined tillage plus residue removal level in this analysis suggests that other combined management practices such as N fertilizer across residue removal levels should be the next focal area of cross-region model validation and assessment, in order to better support the simulation of these management practices within a bioenergy decision support tool framework.

N_2O Emission

The DDcentEVI version of DAYCENT performed more accurately modeling lower annual measured estimates of N_2O flux, as indicated by an insignificant intercept in the regression analysis. However, the slope indicates increasing underestimation of simulated annual flux as measured values increased, which is particularly apparent for sites and years >3-kg N_2O-N ha^{-1} $year^{-1}$ (Fig. 5a). Due to how data were reported, error measurements were only available for some of the treatments and were included to give some visualization of the variability of measured annual N_2O estimates (Fig. 5a). Including error measurements on all the measured annual N_2O emission estimates would help clarify the comparison between modeled and measured values. The model showed an overall bias of underestimating annual N_2O flux, when results were averaged and compared across the residue removal levels (Fig. 5b).

N_2O emissions are highly variable and transient, with high flux occurring often in short time frames following certain events, such as high precipitation, spring thaw, or N fertilizer application. A comparison of daily measured versus modeled N_2O flux shows that the divergence between measured and modeled annual flux may be due, in part, to DAYCENT's failure to capture the presence, timing, or magnitude of transient peak periods (Figs. 6 and 7). For example, in the representative treatment shown in Fig. 6, the model seems to do well in years when soybean is grown and N_2O emissions are consistently low (Fig. 6a, c), perhaps missing a small peak around the harvest period. In comparison, when measured values reflect larger and more frequent peaks during corn growth years, the model performs more variably. In 2009 (Fig. 6b), the model simulations seem to match the timing but not the magnitude of the highest N_2O peak and then missed a peak period at the end of the season, while in 2011 (Fig. 6d), the model simulations seemed to match the magnitude but not the timing of the highest N_2O peak.

Despite the evidence for variable DAYCENT performance simulating transient peak periods of N_2O flux, it is challenging to validate DAYCENT performance either cumulatively or on a daily basis using the discontinuous and sometimes sparse time series of N_2O emission measurements made available in this study. These types of N_2O emission datasets are common, as more frequent measurements taken by hand or by automatic chambers are resource intensive. Where continuous N_2O emission measurements are not possible, discontinuous samples taken at time points aimed to capture transient periods of high flux as well as background flux across the season is a common methodological approach. However, sampling frequency has been recognized to affect cumulative estimates of N_2O emissions, with increasing divergence between true and estimated N_2O emissions as sampling intervals increase in length [51].

In the comparison between DAYCENT modeled estimated and measured values, when N_2O flux changes occur at a time resolution finer than the measured data, the accuracy of DAYCENT simulation between measured data points will remain unclear. This can be observed in the results of this study, with specific examples include the peaks and lows simulated for N_2O emissions between consecutive high measured data points in Figs. 6d (measured data on either side of day 200), 7a (the first two measured data points), and 7b (measured data points on either side of the highest simulated peak). As another example, while the highest measured peak in Fig. 6d is comparable to the modeled peak in magnitude, it is unknown whether the model is simulating the peak too early or whether the measurement was taken as the flux was coming down from a higher peak (Fig. 6).

There is an additional potential for sparse, discontinuous N_2O measurements to overestimate annual flux, depending on the resolution and timing of the measured data and the method of integration used to generate an annual estimate. For example, measured time points might miss a peak or a period of low emissions between peaks or might miss the timing with which a transient peak returns to a baseline flux. The first two data points in Fig. 7a demonstrate this potential; if the period of low emissions simulated by DAYCENT did occur at that site, but is not considered in the integration of the two measured data points to estimate total flux for that period, their integration will result in an overestimation of N_2O flux. It is possible that DAYCENT's underestimation of high N_2O flux may be due to how the measurement data were integrated to determine cumulative emissions. However, it should be noted that a comparison of continuous versus discontinuous N_2O emission measurements demonstrated a pattern of *underestimation* of cumulative emissions using discontinuous data, due to failure to capture transient peaks in the time interval between measurements [52]. In this latter case, DAYCENT simulations of N_2O emissions would diverge even further from measured estimates in years with high flux. Without data at a higher temporal resolution, it is not possible to determine either the accuracy of the annual measured estimates or the extent to which DAYCENT simulations diverge from true N_2O emissions.

Due to the transience and the magnitude of N_2O flux changes across the growing season, there would be great benefits in comparing continuously measured N_2O data against DAYCENT model results, in order to inform the magnitude and timing of peak flux events in model simulations as well as more accurately compare annual flux to measured values. For the purposes of using DAYCENT to evaluate the N_2O emissions of different production practices as a sustainability metric, care should be taken not to underestimate the N_2O emissions in systems of potentially high flux.

Conclusion

Overall, DAYCENT had variable performance simulating the impacts of treatments for corn stover harvest included in the five sites used in this analysis, with the greatest accuracy simulating corn stover yields and consistency in capturing management practice impacts on the relationship and direction of change with SOC and corn grain biomass. DAYCENT had variable performance simulating N_2O emissions, with more accurate performance where annual emissions are low. Cumulatively, the model concurred with measured results suggesting little overall grain yield impacts and suggested the potential for negative SOC impacts with corn stover residue removal and conventional tillage. The model has a tendency to underestimate grain yields—particularly in some regions where the model might be overestimating the impacts of water stress—as well as overestimate SOC loss with conventional tillage and underestimate treatments with high N_2O emissions compared with modeled data. These behaviors are important to consider when integrating DAYCENT results into a larger sustainability estimate, where these tendencies could respectively lead to underestimation of corn grain production potential, overestimation of the negative soil C impacts of residue removal and tillage, and underestimation of the emission of N_2O.

Our residue removal and tillage results support the concept of pairing changes in management for corn stover harvest with treatments such as conversion to no till to maintain productivity and soil health. Modeled results suggested the potential for interactive effects between residue removal and tillage. We also suggest that other combined management practices such as fertilizer application and cover crops be included in subsequent analyses of measured and modeled data comparisons, as these are key practices being considered and recommended as large-scale corn stover harvest for bioenergy moves forward.

This study reflects one of the original purposes of the Regional Partnership corn stove project: integrating field data with the predictive modeling of corn stover removal management practices on a regional basis, in order to support the recommendation of sustainable practices to advance a robust bioenergy industry based on corn stover as a feedstock material.

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